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A FINANCIAL DISTRESS PRE-WARNING STUDY BY FUZZY REGRESSION MODEL OF TSE-LISTED COMPANIES

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ABSTRACT

The purpose of this paper is to construct a financial distress pre-warning model for investors and risk supervisors. Through the Securities and Futures Institute Network, we collect the financial data of the electronic companies listing on the Taiwan Security Exchange (TSE) from 1998 to 2005. By binary logistic regression test, we found that financial statement ratios show significant difference in different financial stages. On the other hand, using fuzzy regression model, we construct a rating model of financial administration stages for investors and risk supervisors and found that prediction validity for financial distress companies and total companies by fuzzy regression model are better than binary logistic regression model using our research sample (89.77 and 90.98% vs. 85.27 and 90.30%).

Keywords: risk management, financial distress, pre-warning, binary logistic regression, fuzzy regression model

INTRODUCTION

Usually, investors or risk supervisors get information from corporation's financial statement reports to understand stock investing decision of the manager. However, the data from financial statement reports maybe consist of uncertainty and dilemma. For example, different companies maybe adopt different accounting schemes to create financial statement reports. Thus, the data of financial statement reports are inconsistent. In regards to this concern, if we use clear value to construct pre-warning model, it would increase flaws between predicted result and realized situation regarding financial distress prediction. Hence, fuzzy method is helpful to handle the data to avoid the error on numeral data. The turnover of electrical industry were about 70% of invested stock in Taiwan. So, this article chose electrical industry to be the research target. Sheppard (1994) and Shumway (2001) have introduced the dilemma of matched pairs to construct bankruptcy prediction models. This differs from Beaver (1966) and Altman (1968) who utilized paired sample to construct financial distress model. In the same way, we plan to take all electronic companies to create financial distress prediction model and apply fuzzy regression model to build a financial stage rating model of the electronic stock listing on the Taiwan Security Exchange (TSE) for investors and risk supervisors.

For research process of social science, researchers often use regression model to investigate relations between independent variable (*X*) and dependent variable (*Y*). Traditional regression model assumes that dependent variable is produced by realistic dependent variable and random error. In other words, error term is an uncertain random variable. But in practice, this does not satisfy assumption of "random". For example, we observe the value of dependent variable as multi-subgroup, not a single value, and the observed value is fuzzy phenomenon, but not random phenomenon. Thus, this paper deals with data in terms of fuzzy perspective instead of random perspective. For example, Su and Cheng (1980) indicated that the data of financial statement reports are inaccurate. Furthermore, it is suitable for us to use interval instead of single value for financial variables. Thus, this article apply fuzzy regression model to construct a financial distress pre-warning model for investors and risk supervisors.

Several studies have distinguished the definition of financial distress by two ways. One is based on the criteria of Law (e.g. Altman, 1968; Zmijewski, 1984; Wang, 2000). The other is the dynamic state which is an entrance to a financial distress step by step (e.g. Lau, 1987; Cheng & Li, 2003). Furthermore, Cheng and Li (2003) found that applying dynamic financial distress to erect pre-warning model could get better prediction validity. As a consequence, this article modified Lau (1987) financial administration stages to build financial pre-warning model for Taiwan electronic industry. We found that most of the companies are in financial stability stage, and few companies are in heavy financial distress stage in Taiwan. Due to lack of sample in distress stage, we expect that it will restrict the forecast validity and bear the drawbacks for pre-warning model. We therefore modify the five financial administration stages proposed by Lau as financial stability stage and financial distress stage, and then use fuzzy regression model to analyze research financial data. We assure that the above modifications will reduce estimation errors and improve forecast validity. The purposes of this research are as follows:

1. Using binary logistic regression method to detect financial statement ratios that have significant difference in different financial stages.
2. Combining fuzzy regression method to construct financial distress pre-warning model of the electronic companies listed on the TSE.

The rest of the paper is organized into several sections. Section 2 introduces the literature of financial distress pre-warning model and fuzzy regression research. Section 3 demonstrates analytic methods and data source. Section 4 presents the results of binary logistic regression and fuzzy regression model. In the end, this study concludes with discussion and summary.

LITERATURE REVIEW

After referring to most academic studies of financial distress definitions, we classify financial administration stages into static state and dynamic state. The former is based on the criteria of law. For instants, Altman (1968) concluded that the definition of financial distress is liquidated or bankrupt. Zmijewski (1984) used criterion of Law (like Chapter X/XI) as financial distress definition. Several scholars, such as Zavgren (1985) and Daniel (1998), are in favor of the same definition.

On the other hand, the financial distress definition of the dynamic state describes different degree of firm financial distress. For example, Beaver (1966) defined financial distress as any of the following events: bankruptcy, bond default, bank account overdrawn, or nonpayment of a preferred stock dividend. Foster (1978) reported that the financial distress stages included four stages: (1) decreasing power of the major products; (2) debts delayed to pay off; (3) omitting priority stock dividend payment; and (4) bond default and bankruptcy. Chen (1983) applied the financial framework of Argenti and Alves's that includes three states: (1) financial distress: insufficient cash flows; poor turnovers; debts delayed to pay off; (2) financial imbalance: temporal inadequate cash turnovers; default on check payments; bond default; and (3) bankruptcy: total debts over total assets; inability to pay off debt. Lau (1987) classified a firm into a five-state financial distress, that is, state 0: financial stability; state 1: omitting or reducing dividend payments more than 40% below previous year; state 2: technical default and default on loan payments; state 3: protection under the Bankruptcy Act; and state 4: bankruptcy and insolvency. Some other researchers, such as Deakin (1972), Blum (1974), Scott (1981), and Laitinen (1991) also used dynamic state to define financial distress. Furthermore, Cheng and Li (2003) found that prediction validity could get better if dynamic financial distress definition was applied to erect pre-warning model. In consequence, this article modified Lau's (1987) financial administration stages as financial stable and financial distress stages to build financial pre-warning model for Taiwan electronic industry.

Prediction of bankruptcy occupies a long and accomplished history. Finance and microeconometrics are occupied with bankruptcy and financial distress topics since Altman (1968) and Beaver (1966) published their seminal articles. Numerous studies and surveys derived various paths from the Altman and Beaver's approaches. Major trends have been developed as follows. Beaver (1966) early used the dichotomous classification test of individual ratios to differentiate between failed and non-failed firms and many domestic scholars accepted and applied his study. Altman (1968), Mensah (1984), Zavgren (1985) and Michael and Constantin (1999) used factor analysis and discriminated analysis to build pre-warning model of financial distress. The studies of Ohlson (1980), Lo (1986), Platt and Platt (2002), and Cheng, Wu, and Li (2006) build a logit model to analyze pre-warning model. Odom and Sharda (1990), Coats and Fant (1993), Zhang, Patuwo, and Hu (1998), and Daniel (1998) used artificial neural network to build models. The results of various methods such as discriminant analysis, logistic regression model and artificial neural network model proved that the predictive power of financial distress is getting better. After reviewing many studies of financial distress pre-warning model, we found that rare studies utilize fuzzy regression model to construct financial distress pre-warning model. Thus, this article utilizes fuzzy regression model to construct and test the pre-warning model of the financial administration stages for investors and risk avoiders.

RESEARCH DESIGN

Business Administration Stages

In order to have good sample size for each stage of the financial distress companies, we modify Lau's (1987) "five stages of financial distress". According to Lau's classifications, states 0 to 4 are states of increasing severity of financial distress and firms can be classified more easily in state 0, state 1, state 2 and state 4. We noted that state 3 of Lau's definition is related to the protection of the Bankruptcy Act under Chapter X or XI.

Correspondently, we adjust the criteria of law in Taiwan based on Chapter X or XI. As there are few heavy distress companies in Taiwan, the sample data are not enough to construct financial pre-warning model and it could make mistakes in statistic inference. We therefore reclassify the companies into two categories: financial distress stage and financial stability stage. The financial distress stages include stages 1 to 4 (see Table 1).

Although the financial stability firm may reduce or omit dividends to finance capital investments, empirical studies by Dielman and Oppenheimer (1984) and Gentry, Newbold, and Whitford (1985) have shown that a firm which reduce dividends typically encounter financial distress. Therefore, we employ "dividends omission or reduction" to represent a financial condition between stages 0 and 2.

Table 1
Definition of Financial Administration Stages

Stages of financial administration	Definition description	Degree of financial crisis
State 0	Financial stability	Financial stability
State 1	Omitting or reducing dividend payments more than 40% over the previous year	
State 2	Technical default and default on loan payments	Financial distress
State 3	Protecting under Chapter X or XI of the Bankruptcy Act	
State 4	Bankruptcy and liquidation	

Research Sample and Data Source

Research sample

We collect the financial data of the electronic companies on the TSE from 1998 to 2005 via the Securities and Futures Institute network. We use the financial statement ratio data from 1998 to 2002 as in-sample data to construct the financial pre-warning model and from 2003 to 2005 as out-of-sample data to evaluate the prediction rate accuracy of the financial pre-warning model.

Financial statement ratio data

The financial dimensions of financial statement include "financial structure", "debt ability", "administration ability", "profit ability", and "cash flow". Financial statement ratios are presented in Table 2.

Research Method

This article uses binary logistic regression and fuzzy regression model to construct and test the financial distress pre-warning model. Both empirical regression methods are described as follows.

Table 2
Financial Statement Ratios

Category	Code	Financial variables	Definition of financial variables
Financial structure	R1	Shareholders' equity to total assets ratio (%)	Total shareholders' equity/total assets
	R2	Debt to total assets ratio (%)	Total liabilities/total assets
	R3	Permanent capital to fixed assets ratio (%)	(shareholders' equity + long debt)/ fixed assets
Liquidity	R4	Current (%)	Current assets/current liabilities
	R5	Acid-test ratio (%)	Cash + cash equivalents + marketable securities + accounts receivable/ current liabilities
	R6	Times interest earned	Interest before income taxes and interest expense/interest expense
Asset utilization	R7	Accounts receivable turnover	Sales/average accounts receivable
	R8	Collection period	360/accounts receivable turnover
	R9	Sale inventory turnover	Operation cost/average sale inventory
	R10	Days to sale inventory	360/sale inventory turnover
	R11	Fixed asset turnover	Sales/average fixed assets
	R12	Total asset turnover	Sales/average total assets
Profitability	R13	Return on assets (%)	Net income + interest expense (1 – tax rate)/average total assets
	R14	Return on common equity (%)	Net income/average shareholders' equity
	R15	Operate profit to capital (%)	Operation income/capital
	R16	Pre-tax profit to capital (%)	Pre-tax income/capital
	R17	Net profitability ratio (%)	After-tax profit/operation revenue
	R18	Earnings per share	(after-tax income – preferred dividends)/the weight numbers of stock
Cash flow	R19	Cash flow ratio (%)	Net cash flow from operation/current liabilities
	R20	Cash flow adequacy ratio (%)	Net cash flow from operation (five years recently)/capital expenditure + increasing amount of sale inventory + cash dividend (five years recently)
	R21	Cash reinvestment ratio (%)	(net cash flow from operation – cash dividend)/(fixed asset + long-term investment + other assets + working capital)

Binary logistic regression

For the binary logistic regression, we use the degree of financial crisis including financial distress and financial stability as dependent variables, and financial statement ratios as independent variables. Then, the binary logistic regression is estimated to construct the financial distress pre-warning model. It is presented in Equation (1).

$$y^* = \alpha + \sum_{i=1}^{K} \beta_i R_i + \varepsilon \, . \tag{1}$$

If $y^* \leq \mu_1$, then y denotes financial stability stage.
If $y^* > \mu_1$, then y denotes financial distress stage.
y^* is a theorical value and y is an observed value.
α = constant; β_i = regression estimators, i = 1, 2, …, K
R_i = financial statement ratios variables, i = 1, 2, …, K; ε = error term.

Fuzzy regression model

Tanaka et al. (1982) were the first to propose an alternative concept of fuzzy regression model. The formulas of fuzzy regression model are presented as follows:

$$Y(x_i) = A_0 + A_1 x_{1i} + A_2 x_{2i} + \cdots + A_p x_{pi} \tag{2}$$

where $x_i = (1, x_{1i}, x_{2i}, ..., x_{pi})'$ is the vector of independent variables, $Y(x_i)$ is the fuzzy dependent variables, and A_m, m = 0, 1, 2, ..., p are fuzzy parameters. We assume the function of A_m is trigonal style as in Equation (3).

$$u_{A_m}(t) = \max\left\{1 - \frac{|t - c_m|}{s_m}, \; 0\right\}, \; -\infty < t < \infty \tag{3}$$

where c_m is the middle of triangle, s_m is the radius of triangle. We depict c_m, s_m, and function ($u_{A_m}(t)$) in Figure 1.

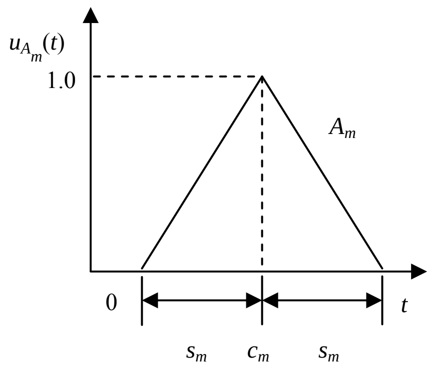

Figure 1. Triangle function

Let fuzzy parameter A_m belong to (c_m, s_m), and Equation (2) can be rewritten as:

$$Y(x_i) = \langle c_0, s_0 \rangle + \langle c_1, s_1 \rangle x_{1i} + \langle c_2, s_2 \rangle x_{2i} + \cdots + \langle c_p, s_p \rangle x_{pi}. \qquad (4)$$

Thus, the function of fuzzy dependent variables $Y(x_i)$ is pertained to trigonal style as in Equation (5).

$$u_{Y(x_i)}(t) = \max \left\{ 1 - \frac{\left| t - \sum_{m=0}^{p} c_m x_{mi} \right|}{\sum_{m=0}^{p} s_m |x_{mi}|}, 0 \right\}, \ -\infty < t < \infty. \qquad (5)$$

This article is consistent with the characteristics of the ordinary least square (OLS) estimator to generate fuzzy regression estimator formula. The formulas of the fuzzy regression estimator are described in Equations (6) to (12).

We take all left points to formulate left-estimation of fuzzy regression model. The left-estimation of fuzzy regression model is presented in Equation (6).

$$Y_L(x_i) = \hat{L}_0 + \sum_{m=1}^{P} \hat{L}_m x_m, \ i = 1, 2, ..., n \qquad (6)$$

where L_m is the regression estimator.

Then, we take right points $\{(x_i, y_{Li}): i = 1, 2, ..., n\}$ to create right-estimation of fuzzy regression model. The right-estimation of fuzzy regression model is presented in Equation (7).

$$Y_R(x_i) = \hat{R}_0 + \sum_{m=1}^{P} \hat{R}_m x_m,\ i = 1, 2, ..., n \tag{7}$$

where R_m is the regression estimator. Combining Equations (6) and (7), we can obtain Equation (8).

$$\left[\hat{Y}_{(x_0)}\right]^H = \left[\hat{L}_0 + \sum_{m=1}^{P} \hat{L}_m x_m,\ \hat{R}_0 + \sum_{m=1}^{P} \hat{R}_m x_m\right]. \tag{8}$$

The function of $Y(x_i)$ is displayed as in Equation (9).

$$u_{Y(X_i)}(t) = \max\left\{1 - \frac{\left|t - \sum_{m=0}^{p}(\frac{\hat{R}_m + \hat{L}_m}{2})X_{mi}\right|}{\sum_{m=0}^{p}(\frac{\hat{R}_m - \hat{L}_m}{2(1-H)})\left|X_{mi}\right|},\ 0\right\},\ -\infty < t < \infty. \tag{9}$$

In addition, let $x_{0i} = 1$, we can derive function of fuzzy parameter (A_m) as in Equations (10) and (11).

$$u_{A_m}(t) = \max\left\{1 - \frac{\left|t - (\hat{R}_m + \hat{L}_m)/2\right|}{(\hat{R}_m - \hat{L}_m)/2(1-H)},\ 0\right\}. \tag{10}$$

Through Equation (10), we can get Equation (11). $\frac{\hat{R}_m + \hat{L}_m}{2}$ is the middle point of triangle. $\frac{\hat{R}_m - \hat{L}_m}{2(1-H)}$ is the radius.

$$A_m = \left\langle \hat{R}_m + \hat{L}_m / 2,\ \hat{R}_m - \hat{L}_m / 2(1-H) \right\rangle. \tag{11}$$

Finally, through Equation (11), we apply OLS to estimate parameter of fuzzy regression model and obtain the estimated model as Equation (12). The interval of intercept is $\{(R_0 + L_0)/2, (R_0 - L_0)/2(1 - H)\}$, and the interval of each slope is $\{(R_i + L_i)/2, (R_i - L_i)/2(1 - H)\}$.

$$\tilde{Y}_{(x_0)} = \left\langle \frac{\hat{R}_0 + \hat{L}_0}{2}, \frac{\hat{R}_0 - \hat{L}_0}{2(1-H)} \right\rangle + \left\langle \frac{\hat{R}_1 + \hat{L}_1}{2}, \frac{\hat{R}_1 - \hat{L}_1}{2(1-H)} \right\rangle x_{1i} + \left\langle \frac{\hat{R}_2 + \hat{L}_2}{2}, \frac{\hat{R}_2 - \hat{L}_2}{2(1-H)} \right\rangle x_{2i} + \ldots + \left\langle \frac{\hat{R}_p + \hat{L}_p}{2}, \frac{\hat{R}_p - \hat{L}_p}{2(1-H)} \right\rangle x_{pi} \tag{12}$$

From Equation (12), we can get the interval on slope of each independent variable. Also, we can understand the correlation between dependent variable and independent variables from the slope value.

Research Restrictions

The major limitation of this article is that the financial statement ratios variables are the only information used to build financial distress pre-warning model, but the non financial variables such as stock structure and business cycle factors, etc., are not specified. Also, as the financial data of the electronic companies listed on the TSE are the right research sample, the research consequences thus could not fit other industries.

RESULTS

Data Analysis

To avoid downgrading the prediction ability of financial pre-warning model due to the variance of financial statement ratio changes, we perform the description statistic analysis of the twenty-one financial statement ratios to search over-variance financial statement ratios. Then, we use mean and standard deviation to examine the stability of different administration stages. The description statistic analysis of the financial statement ratios is presented in Table 3.

After completing the description statistic analysis of financial statement ratios such as permanent capital to fixed assets ratio (R3), times interest earned ratio (R6), collection period ratio (R8), sale inventory turnover ratio (R9), total asset turnover ratio (R12), return on common equity ratio (R14), and net profitability ratio (R17), we find the standard deviation of financial stability stage and financial distress stage are over different. If we apply over-variance financial statement ratio to estimate the range of financial stability and financial distress stage, it would generate overlap range between financial stability and financial distress stage. Thus, we eliminate these seven financial statement ratios in conducting the binary logistic regression analysis.

Table 3
Financial Statement Ratios Statistic Analysis

Category	Code	Financial variables	Financial stability		Financial distress	
			Mean	Std. Dev.	Mean	Std. Dev.
Financial statement	R1	Shareholders' equity to total assets ratio	64.91	12.54	55.67	16.17
	R2	Debt to total assets ratio	35.15	12.62	44.39	16.20
	R3	Permanent capital to fixed assets ratio	558.98	441.80	548.54	988.47
Liquidity	R4	Current	240.46	161.32	176.08	141.10
	R5	Acid-test ratio	190.51	144.81	132.91	131.49
	R6	Times interest earned	740.80	2876.16	–10.36	199.95
Asset utilization	R7	Accounts receivable turnover	5.45	2.23	4.26	1.93
	R8	Collection period	76.21	30.75	106.14	66.39
	R9	Sale inventory turnover	9.64	8.74	11.64	35.37
	R10	Days to sale inventory	63.03	64.06	78.38	61.73
	R11	Fixed asset turnover	8.52	9.40	7.47	11.79
	R12	Total asset turnover	0.97	0.58	1.02	2.80
Profitability	R13	Return on assets	10.96	6.39	–3.10	9.26
	R14	Return on common equity	15.83	9.51	–11.16	25.33
	R15	Operate profit to capital	26.17	27.09	–0.93	15.49
	R16	Pre-tax profit to capital	32.82	27.44	–9.90	22.38
	R17	Net profitability ratio	12.82	10.35	–6.17	75.91
	R18	Earnings per share	3.31	4.21	–1.06	2.51
Cash flow	R19	Cash flow ratio	53.06	67.81	30.11	43.06
	R20	Cash flow adequacy	70.43	72.88	42.95	56.80
	R21	Cash reinvestment ratio	9.71	9.93	7.80	14.43

Binary Logistic Regression Results

Through binary logistic regression test, we find the financial statement ratios that have significant difference in different financial stages. Then, we utilize the significant financial statement ratios verified by logistic regression to perform fuzzy regression model and construct a rating model of financial administration stages. The consequences of binary logistic regression test are displayed in Tables 4 to 6.

Model significant test

First, we examine the fit of binary logistic regression model. The outcome presents that there is a significant effect between independent variables and dependent variables ($p < 0.05$). The fit of binary logistic regression model is presented in Table 4.

Table 4
Fit of Binary Logistic Regression Model

Model	–2 Log Likelihood	χ^2	*p*-value
Final	275.555	94.365	0.000^{***}

Note: *** $p < 0.001$

Detecting financial statement ratios

We utilize binary logistic regression method to detect the financial statement ratios. Table 5 presents the regression result. The result indicates that the financial statement ratios such as return on total assets (R13) and cash flow adequacy ratio (R20) have significant difference in different financial stages.

Table 5
Test of Binary Logistic Regression

Category	Code	Financial variables	Estimators	*p*-value
Profit ability	R13	Return on total assets	–0.572	0.000^{***}
Cash flow	R20	Cash flow adequacy ratio	0.007	0.002^{**}
Constant			2.078	

Notes: $^{**}p< 0.01$, $^{***}p< 0.001$

Besides, the negative estimated parameter of return on total assets indicates that there is a negative effect between return on total assets and financial stages. On the other hand, if ROA is lower, the possibility of turning into financial distress stage is higher. Moreover, as companies often employ cash flow adequacy ratio to adjust the financial balance, errors by corporation size and industry inventory may exist Thus, we will not discuss the parameter estimator of cash flow adequacy ratio.

Furthermore, if the return on total assets decreased by 1%, the risk of financial distress of corporation occurrences would increase by 1.772 ($e^{0.572}$) multiple. If the cash flow adequacy ratio increased by 1%, the risk of financial distress of corporation occurrences would increased by 1.007 ($e^{0.007}$) multiple.

The estimation result of the binary logistic regression model is presented as follows:

$$\text{Logit } Y = 2.107 - 0.568X_1 + 0.007X_2.$$

The prediction validity of binary logistic regression

The prediction validity of financial distress companies and financial stable companies are 85.27 and 93.91%, respectively. Total prediction validity of all companies is 90.30%. The result is presented in Table 6.

Table 6
Rate of Prediction Accuracy of Binary Logistic Regression

	Prediction		
Realistic	Financial stability	Financial distress	Accurate prediction rate (%)
Financial stability	293	19	93.91
Financial distress	33	191	85.27
Percentage			90.30

Fuzzy Regression Model

The fuzzy regression model is consistent with the characteristics of the OLS method, which is the best linear unbiased estimator to generate left and right fuzzy regression estimator. We use the minimum and maximum data of return on total assets and cash flow adequacy ratio as the independent variables. On the other hand, we use the minima and maximum prediction value of binary logistic regression model as the dependent variable.

Applying in-sample data from 1998 to 2002, we construct fuzzy regression model of the electronic stock listing on the TSE and applying out-of-sample data from 2003 to 2005, we test the fuzzy regression model. The left-estimation formula, right-estimation formula, and fuzzy regression model estimation as well as test are described in the following sections.

The left-estimation of fuzzy regression model

According to prior studies, the H value should be between 0.1 to 0.5. In order to let dependent variable fit to fuzzy regression, this article uses middle value (0.3) to estimate left and right fuzzy regression model. We apply the OLS method to generate fuzzy regression formula. The left-estimation of fuzzy regression model is presented as follows:

$$y_L(x_i) = \sum_{j=0}^{2} L_j x_{ji} = 2.027 - 0.289x_{1i} + 0.004x_{2j}.$$

Table 7
Left-Estimation of Fuzzy Regression Model

Explanatory variables	Estimators	Standard	*t*-value	*p*-value
Constant	2.027	0.528	3.842	0.000^{***}
Return on total assets	–0.289	0.039	–7.492	0.000^{***}
Cash flow adequacy ratio	0.004	0.008	0.513	0.608
$F = 34.246^{***}$		$R^2 = 28.25\%$		

Note: *** $p < 0.001$

From Table 7, we found that the return on total assets (ROA) has significant difference in different financial stages (p-value < 0.05). But the cash flow adequacy ratio has no significant difference in different financial stages (p-value > 0.05). In addition, using regression parameter estimation, we found that there is a negative effect between return on total assets and financial stages and there is a positive effect between cash flow adequacy ratio and financial stages. On the other hand, if ROA is greater, the possibility of turning to financial stability stage is higher. And if the cash flow adequacy ratio is lower, the possibility of turning to financial stability stage is higher.

The right-estimation of fuzzy regression model

We apply the OLS method to generate fuzzy regression formula, the right-estimation of fuzzy regression model is depicted as follows:

$$y_R(x_i) = \sum_{j=0}^{2} R_j x_{ji} = -1.432 - 0.110x_{1i} + 0.009x_{2j}.$$

Table 8
Right-Estimation of Fuzzy Regression Model

Explanatory variables	Estimators	Standard	*t*-value	*p*-value
Constant	–1.432	0.592	–2.419	0.012^{*}
Return on total assets	–0.110	0.043	–2.576	0.009^{**}
Cash flow adequacy ratio	0.009	0.006	1.395	0.165
	$F = 8.396^{**}$		$R^2 = 28.67\%$	

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$

From Table 8, we found that the return on total assets has significant difference in different financial stages (p-value < 0.05). But cash flow adequacy ratio has no significant difference in different financial stages (p-value > 0.05).

We eliminate the cash flow adequacy ratio to construct the financial rating model and it resulted in no significant difference in different financial stages for left-estimation and right-estimation of fuzzy regression model. In consequence, the financial rating model is constructed by fuzzy regression model using the return on total assets. The results are displayed in Table 9.

Table 9
The Parameter Estimation of Fuzzy Regression Model

Explanatory variables	Estimators	Standard	t-value	p-value
Constant (left)	1.869	0.427	4.374	0.000^{***}
Return of total assets (left)	–0.297	0.036	–8.277	0.000^{***}
Constant (right)	–2.099	0.540	–3.892	0.000^{***}
Return of total assets (right)	–0.134	0.043	–3.149	0.002^{**}

Notes: $^{**}p < 0.01$, $^{***}p < 0.001$

The forecast model of fuzzy regression model

Applying Equations (11) and (12), we can calculate the fuzzy parameters of A_i (A_0: (1.869, –2.099) and A_1: (–0.297, –0.134)) and then the formulas of fuzzy regression model is formed as follows:

$$Y_i = (-0.115, -2.834) + (-0.216, 0.116)\, X_{i1}.$$

Next, we use the return on total assets of the stock listing electronic companies from 1998 to 2002 as in-sample data to test the fuzzy regression model and then estimate the range of financial stability and financial distress. The two rules to judge the financial stages are as follows:

1. If the fuzzy value is less than –1.54, we consider that the corporation is in the financial stability stage.
2. Else, we consider that the corporation is in the financial distress stage.

Finally, we exploit estimated values to examine its prediction rate accuracy for the research data from 1998 to 2002. We take the return on total assets and cash flow adequacy ratio to calculate the fuzzy value. If the fuzzy value is less than –1.54, we consider that the corporation is in the financial stability stage. Else, we consider that the corporation is in the financial distress stage. The prediction rate accuracy of in-sample for fuzzy regression analysis is shown in Table 10.

Table 10
In-Sample Data Prediction Accuracy for Fuzzy Regression

Realistic	Prediction: Financial stability	Prediction: Financial distress	Accurate prediction rate (%)
Financial stability	287	25	91.99
Financial distress	26	198	88.39
Percentage			90.49

The prediction validities for financial distress companies and financial stable companies are 88.39 and 91.99%, respectively and the total prediction validity for all companies is 90.49%. Moreover, the examined results indicate that there is a negative effect between return on total assets and financial stages and there is a positive effect between cash flow adequacy ratio and financial stages. It means that if ROA is greater, the possibility of turning to financial stability stage is higher. And if the cash flow adequacy ratio is lower, the possibility of turning to financial stability stage is higher.

The forecast validity of fuzzy regression model

We use the return on total assets of the electronic companies listing on TSE from 2003 to 2005 to perform the out-of-sample test of the fuzzy regression model. This will give us estimated values. Then, we utilize estimated values to examine its prediction rate accuracy. The prediction rate accuracy of out-of-sample for fuzzy regression analysis is presented in Table 11.

Table 11
Out-of-Sample Data Prediction Accuracy for Fuzzy Regression Analysis

Realistic	Prediction: Financial stability	Prediction: Financial distress	Accurate prediction rate (%)
Financial stability	316	29	91.59
Financial distress	18	158	89.77
Percentage			90.98

The prediction validity for financial distress companies and financial stable companies are 89.77 and 91.59%, respectively and the prediction validity for total companies is 90.98%. In addition, the fuzzy regression model generally provides lower type I error rates than binary logistic regression method. It means that applying fuzzy regression model to construct financial distress pre-warning model will produce better forecast validity than binary logistic regression method.

DISCUSSION AND SUMMARY

The primary objective of this article is to construct a better financial stage pre-warning model for financial distress as an alternative to well-known methods, namely discriminant, logit and artificial neural network analysis and then investigate the applicability to electrical industry in Taiwan.

The financial data of the electronic companies listed on the TSE are collected from 1998 to 2005 via the Securities and Futures Institute Network. From the binary logistic regression test, we found that the financial statement ratios, such as return on total assets and cash flow adequacy ratio show significant difference in different financial stages.

The result is consistent with previous studies (e.g. Altman, Haleman, & Narayanan, 1977). Also, the estimated coefficients of model indicate that if the return on total asset decreases by 1%, the risk of the financial distress of corporation occurrences would multiply 1.772 times and if the cash flow adequacy ratio increased by 1%, the risk of the financial distress of corporation occurrences would multiply 1.007 times. Finally, we use the fuzzy regression model to construct an evaluation model of financial administration stages for investors and risk avoiders. As a result, the prediction validity of financial distress companies and financial stable companies are 89.77 and 91.59%, respectively. On the other hand, the forecast validity of total companies is 90.98%.

The results of this study are favorable in comparison with other studies. Cheng, Li, and Yeh (2006) who used the non-parameter and bootstrap analysis found that the financial stages could classify 84% of electrical firms correctly. Cheng, Wu, and Li (2006) who used multinomial logit model found that the accuracy rates of plastic firms and electrical firms are 87 and 88%, respectively. Remarkably, the forecast validities of our financial stage pre-warning model that uses binary logistic regression and fuzzy logistic regression are better than Cheng, Li, and Yeh (2006) and Cheng, Wu, and Li (2006). Thus, we suggest that future researchers who investigate financial distress pre-warning model to refer to fuzzy regression method to get better forecast validity or explanatory ability.

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